Bayesian analysis of latent variable models in finance

Barra, I.

2016

Chapter 5

Summary

In this thesis we have dealt with the Bayesian analysis of nonlinear, non-Gaussian state space models in the field of financial econometrics. Estimating nonlinear, non-Gaussian state space models boils down to evaluating a high dimensional integral as the likelihood of these models is defined in terms of an integral. The evaluation of the likelihood is challenging, because it can not be calculated by using a closed form expression. We have to use numerical integration methods. It turns out that a class of numerical integration methods called Monte Carlo integration is especially useful to carry out these computations because it's accuracy does not directly depend on the dimension of the integral, which is typically quite high in these applications. We have used or discussed different ideas to facilitate the use of Monte Carlo methods such as adaptive proposals, resampling, tempering, and auxiliary mixture sampling to name a few. We have used these methods to estimate various models in financial econometrics such as stochastic volatility models for daily stock returns, dynamic credit risk models and integer valued stochastic volatility models for high frequency trade by trade returns.

In Chapter 2 we have proposed a Bayesian estimation procedure for general nonlinear, non-Gaussian state space models. The method depends on a flexible mixture of Student's t proposal distribution, which minimizes the Kullback-Leibler divergence between the target posterior distribution and the mixture of Student's t proposals. We have shown that our method is a black box procedure and does not need case by case design as standard Markov Chain Monte Carlo procedures. We have demonstrated the efficiency of our method in simulation experiments on stochastic intensity and stochastic volatility models based on Ornstein–Uhlenbeck processes. We have given some evidence that in terms of efficiency our method is comparable to several recently proposed algorithms such as the SMC^2 by Chopin et al. (2013a) and the density tempered marginalized sequential Monte Carlo estimation procedure by Duan and Fülöp (2015). In our empirical study, we have showed the performance of our methods for corporate default panel data and stock index returns.

In Chapter 3 we have dealt with the Bayesian sequential estimation of dynamic credit risk models and shown that how it can help to explain the variation in corporate credit spreads. We have explained part of the variation in corporate credit spreads with the variation in ways how agents perceive default risk over time. If there is an unobserved component in corporate default intensities, then part of the fluctuation in corporate bond prices can be attributed to the variation in beliefs about this latent factor. We have shown evidence of a latent frailty factor in terms of Bayes factors, even after accounting for several firm specific and macro variables. We have used the changes in conditional expectations of the frailty level, persistence and volatility as a proxy for changes in agents beliefs about the unobserved factor. We demonstrate that changes in frailty related variables help to explain the variation in US corporate credit spreads.

In Chapter 4 we have discussed stochastic volatility models of high frequency trade by trade returns. We have shown that trade by trade high frequency returns are affected by the fact that on most stock exchanges prices are defined on a discrete grid. We have investigated different integer valued distributions which can account for the fat tails of price change distribution. We have proposed an integer valued stochastic volatility model based on the difference of negative binomial random variables. We consider models which explicitly take into account the discreteness of the observed prices, the fat tails of tick returns and the intraday patterns of volatility. We have suggested a Markov chain Monte Carlo estimation method, which takes advantage of data augmentation and auxiliary mixture sampling. Using our model we were able to decompose the volatility into a persistent daily seasonality pattern and an autoregressive component which captures the deviation of volatility from the daily pattern. Finally, we have illustrated our methodology using tick by tick data of several stocks from the NYSE in different periods. Using predictive likelihoods we have found evidence in favour of the dynamic ΔNB model.